AUGMENTING SIMULATIONS OF AIRFLOW AROUND BUILDINGS USING FIELD MEASUREMENTS

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Abstract – Computational fluid-dynamics (CFD) simulations have become an important tool for the assessment of airflow in urban areas. However, large discrepancies may appear when simulated predictions are compared with field measurements because of the complexity of airflow behaviour around buildings and difficulties in defining correct sets of parameter values, including those for inlet conditions. Inlet conditions of the CFD model are difficult to estimate and often the values employed do not represent real conditions. In this paper, a model-based data-interpretation framework is proposed in order to integrate knowledge obtained through CFD simulations with those obtained from field measurements carried out in the urban canopy layer (UCL). In this framework, probability-based inlet conditions of the CFD simulation are identified with measurements taken in the UCL. The framework is built on the error-domain model falsification approach that has been developed for the identification of other complex systems. System identification of physics-based models is a challenging task because of the presence of errors in models as well as measurements. This paper presents a methodology to estimate modelling errors. Furthermore, error-domain model falsification has been adapted for the application of airflow modelling around buildings in order to accommodate the time variability of atmospheric conditions. As a case study, the framework is tested and validated for the predictions of airflow around an experimental facility of the Future Cities Laboratory, called “BubbleZERO”. Results show that the framework is capable of narrowing down parameter-value sets from over five hundred to a few having possible inlet conditions for the selected case-study. Thus the case-study illustrates an approach to identifying time-varying inlet conditions and predicting wind characteristics at locations where there are no sensors.

Keywords: Computational Fluid Dynamics (CFD); airflow modelling; field measurements; system identification; multi-model reasoning

1) INTRODUCTION

Urban populations are growing and therefore, understanding urban climate behaviour has become an increasingly important research field. Urban climate has an impact on the comfort and health of residents. The energy consumption of buildings is influenced by the convective heat flux at the building façade and therefore by the wind pattern around buildings (Defraeye et al., 2011). Furthermore, energy demand of buildings can also be reduced by harnessing airflow for natural ventilation (Ghiaus and Allard, 2005). Therefore, cities and buildings should be planned and designed according to characteristics of their climatic environments.

Computational fluid-dynamics (CFD) simulations have increasingly been used to simulate the airflow in urban areas (Al-Sallal and Al-Rais, 2011; Van Hooff and Blocken, 2010). CFD simulations numerically solve the fluid-flow equations of motion. In general, the equations are time dependent; this
means that flow variables at each point have to be computed at several points in time. Directly solving the equations using numerical methods take much computer memory and time and therefore, simplifications are made to mathematical models. In steady Reynolds-averaged Navier-Stokes (RANS)-based models, the fluid-flow equations of motion are averaged over time. This results in steady-state equations that are easier to solve. Standard k-epsilon and revised k-epsilon models are examples of RANS-based models. In these models, two additional transport equations are employed to model turbulent properties of the flow. For example, in the standard k-epsilon model, the new transported variables are the turbulent kinetic energy \(k\) and turbulent dissipation rate \(\varepsilon\). Another popular approach for modelling turbulence is Large Eddy Simulation (LES) in which time-dependent variations of flow quantities are computed. LES solves large eddies of flow and model the small eddies with a subgrid-scale model. While, this is computationally more efficient than direct numerical solution, it takes significantly greater computation time than RANS-based models.

CFD simulations provide high-resolution data and allow efficient parametric studies for evaluating design configurations (Van Hooff and Blocken, 2010). Due to the increased use of CFD simulations for urban airflow modelling, several sets of best practice guidelines (BPG) have been established (Franke et al., 2011; Tominaga et al., 2008b). However, the accuracy of CFD simulations remains a major concern due to uncertainties associated with i) modelling complex phenomena present in urban environments (Allegrini et al., 2013; Mochida and Lun, 2008; Murakami, 2006), ii) the representation of complex geometrical structures of urban sites and iii) numerical challenges at wall boundaries (Blocken et al., 2007). Even a sophisticated model may not be accurate because of uncertainties in input parameter values such as inlet conditions. For a steady-state model, other significant sources of uncertainties are associated with the time variability of atmospheric conditions (Schatzmann and Leitl, 2011). CFD simulations are thus often validated only with wind-tunnel experiments under controlled experimental conditions (e.g. Ramponi and Blocken, 2012). However, time variability of atmospheric conditions cannot be captured in a conventional wind tunnel in which fixed inlet conditions are employed. In urban environments, many combinations of values of variables such as wind speed, wind direction and turbulent kinetic energy may occur upstream of the area of interest over a short period. The time variability of atmospheric conditions may be estimated using Large Eddy Simulation (LES) with time-dependent inlet conditions. Jiang and Chen found better results using LES with varying wind directions at the inlet rather than using LES with fixed wind directions (Jiang and Chen, 2002). However, LES was only performed during a real-time period of 10-20 min with specific inlet conditions.

Challenges appear if field measurements are used to validate steady-state models (Schatzmann and Leitl, 2011). The averaging period of measurement data should be short enough in order to capture the variations at the inlet of the computational domain. However, if a short averaging period is employed, errors between predicted and measured values are expected because of the stochastic time variations of flow characteristics due to low frequency turbulence (Schatzmann and Leitl, 2011).

Alternatively, field measurements are employed in order to quantify the airflow in urban areas. Measurement values in the Urban Canopy Layer (UCL) depend on the location of the sensor because of high spatial variability of airflow. Significant variations might be observed if measurements are carried out even a few meters apart from each other (Schatzmann and Leitl, 2011). Therefore, field measurements cannot provide the whole image of the airflow pattern as CFD simulations can do.

Model-based data-interpretation strategies have the potential to improve the accuracy of CFD simulations using knowledge obtained from field measurements. In this paper, use of these approaches involves generating sets of CFD simulations through assigning values of parameters that are not known precisely to a model class (template model).
Many approaches exist for the identification of physics-based models using measurements. Deterministic approaches, in which an optimum model is found by minimizing the differences between model predictions and measurements, may not be appropriate to identify parameter values within model classes because many combinations of parameter values may be consistent with the measurement data. Such ambiguities are amplified by uncertainties in models and measurements, particularly when there are several sources of systematic bias. Modelling assumptions often introduce bias.

Moreover, deterministic approaches do not usually provide information on the uncertainties of predictions. Probabilistic approaches, in which many plausible models are found, are more appropriate for identification of environmental models. Their performance depends on the knowledge of the error structure (Beven, 2008). The error structure refers to the probability density function of both measurement and modelling error as well as their spatial correlations. Modelling error originates from uncertainty associated with the model class.

Model-falsification approaches such as Generalized Likelihood Uncertainty Estimation (GLUE) (Beven, 2008; Beven, 2006) and the error-domain model falsification approach (Goulet et al., 2013; Goulet et al., 2012) may be used to identify parameter values of CFD models where knowledge of modelling error is not known precisely. Error-domain model falsification involves falsification of model instances for which the difference between measured and predicted values is, for any measurement location, larger than an estimate of maximal values of error defined by combining measurement and modelling uncertainties at that location. The term model instance refers to an instantiation of a model class with specific values of parameters. Error-domain model falsification has not yet been applied to time varying contexts such as airflow around buildings.

The first objective of this paper is to present a model-based data interpretation framework that is appropriate for CFD simulations in urban areas. More specifically, a systematic approach for determining ranges of possible inlet conditions is described along with a methodology for estimating modelling errors. In this framework, error-domain model falsification is employed and adapted in order to deal with the time variability of airflow. Modelling errors are estimated by comparing responses of simulations using RANS-based model with those of LES. Responses of LES are not perfectly correct. Therefore, only lower bound estimates of modelling errors are determined in this paper. The second objective is to illustrate this framework using a case study of the “BubbleZERO” facility. “BubbleZERO” is an experimental facility of the Future Cities Laboratory, Singapore-ETH Centre for Global Environmental Sustainability located at the National University of Singapore.

The structure of the paper is as follows. In the next section, an overview of the accuracy of CFD simulation for the predictions of wind characteristics in urban areas is provided. A model-based data interpretation framework is proposed in Section 3. Section 4 introduces the case study as well as the set of numerical simulations used in the model-based data interpretation framework. In Section 5, the sensor setup for the case study is described. Section 6 presents a methodology to evaluate modelling errors. Section 7 completes the case study by applying the model-based data interpretation framework to measurement and simulation datasets. The paper ends with a discussion of results, limitations and plans for future work.

2) SOURCES OF UNCERTAINTIES IN NUMERICAL SIMULATIONS

Several studies have evaluated the performance of RANS-based models for prediction of mean flow quantities around buildings. These studies usually compare responses of numerical simulations with wind tunnel experiments. The advantage of wind tunnel experiments for validation of CFD simulations is that values of simulation parameters and boundary conditions are well known. Hence, if numerical errors are negligible, conclusions related to the performance of the turbulence model can be made. An
extensive validation study was carried out by Yoshie et al. for the development of the Architectural Institute of Japan (AIJ) guidelines (Yoshie et al., 2007). Comparison between simulations using RANS-based models and wind tunnel experiments have been performed for four building geometries, 1) Airflow around a single idealized building with ratio length:width:height=1:1:2, 2) Airflow around an idealized high-rise building with ratio length:width:height=1:1:4 surrounded by low-rise buildings, 3) Airflow in the urban area of Niigata in which CAD data were used, 4) Airflow in the urban area of Shinjuku in which CAD data were used.

In the study of the airflow around a single idealized building with ratio length:width:height=1:1:2, responses of CFD simulations using the standard k-epsilon model or revised k-epsilon models have been compared with wind tunnel measurements carried out by Meng and Hibi (1998). It was found that predicted values of amplification factor of wind speeds, $U/U_0$, are in good agreement ($\pm 10\%$) with measured values in regions of high wind speeds ($U/U_0>1$). The amplification factor of wind speeds is defined as the ratio between the local wind speed, $U$, to the wind speed, $U_0$, that would occur without the presence of buildings. However, in low wind speeds regions ($U/U_0<1$), CFD simulations underestimate the amplification factors of wind speeds by a factor 5 or more (Blocken et al., 2011).

Revised k-epsilon models provide slightly more accurate responses in regions of high wind speeds but less accurate responses in regions of low wind speeds. The reverse flow on the roof is not reproduced with the standard k-epsilon model while the reverse flow is slightly overestimated with revised k-epsilon models (Yoshie et al., 2007). Overestimation of the region of reverse flow in the wake of the building is observed for all RANS-based models.

The same measurement data were used by Tominaga et al. (2008a). In this study, measurements were compared with responses of simulations using RANS-based models (standard k-epsilon model and revised k-epsilon models) as well as responses of LES with and without inflow turbulence. The estimation of the size of the reverse-flow region in the wake of the building is improved if LES is employed (Tominaga et al., 2008a). Responses of LES with inflow turbulence were found to be in good agreement with wind tunnel experiments when predicting mean velocity and turbulent kinetic energy in the wake of the building.

Yoshie et al. had similar conclusions for the three other building geometries (Yoshie et al., 2007): in regions of high wind speeds, predicted amplification factors of wind speeds are fairly accurate ($\pm 10\%$-$20\%$). However, large errors in the predictions of amplification factors are observed in regions of low wind speeds (factor 4-5 or more).

Blocken and Carmeliet compared responses of simulations using the Realizable k-epsilon model (Shih et al., 1995) (RANS-based model) with sand-erosion wind-tunnel experiments carried out by Beranek (1979) for three configurations of parallel buildings (Blocken and Carmeliet, 2008). A grid-sensitivity analysis has been performed and high-order discretisation schemes were employed in order to reduce numerical errors. The results confirmed that performance of the RANS-based model in the predictions of amplification factors is higher in regions of high wind speeds ($\pm 10\%$ accuracy). Simulations using the RANS-based model significantly underestimate the amplification factor in regions of low wind speeds (factor 4 or more).

Incorrect definition of parameter values/inlet conditions may also lead to uncertain predictions of wind characteristics. Inlet conditions of CFD simulations are difficult to estimate. Even if a measurement station is employed to measure the inlet boundary conditions, the measurements may not be representative of the overall conditions at the inlet because of the high spatial variability of wind characteristics in the UCL (Schatzmann and Leitl, 2011). Even above the buildings, spatial variability
is observed because the airflow is constantly adapting to the change of surface characteristics (Schatzmann and Leitl, 2011).

Buildings are modelled with a certain degree of geometrical simplification in CFD simulations. An equivalent roughness is imposed at building surfaces. The equivalent surface roughness of the surrounding buildings is difficult to estimate and may have a strong influence on predictions of wind speeds (Blocken and Persoon, 2009). In a previous study, field measurements have been used in order to estimate the value of the roughness of the surrounding buildings that leads to the best fit (Blocken and Persoon, 2009). However, as mentioned previously, while calibration approaches force matches of model predictions with measurement data at locations of sensors, they may not be accurate at other locations.

3) METHODOLOGY

3.1) Description of the system variables

This Section presents the model-based data-interpretation framework used to identify plausible parameter values of CFD simulations through measurements carried out in the urban canopy layer. The framework is an adaptation of the error-domain model falsification approach developed by Goulet (Goulet et al., 2013; Goulet et al., 2012).

The first step is to define the parameters that need to be identified \( \theta = [\theta_1, ..., \theta_{\text{max}}] \) with measurements \( y \) and their prior ranges of values. In this study, boundary conditions such as the inlet wind speed and direction are treated as parameters of the model. Then, a population of model instances \( M(\theta_j) \) is generated through assigning a set of parameter values \( \theta_j \) to a model class \( M \) with \( j \in \{1, ..., n_m\} \), where \( n_m \) corresponds to the number of model instances generated.

When the right set of parameter values \( \theta^* = [\theta_1^*, ..., \theta_{\text{max}}^*] \) is assigned to the model class \( M \), the predictions of the model instance \( M(\theta^*) \) correspond to the real quantity \( Q \) plus a modelling error \( \epsilon_{\text{model}} \). Modelling errors are errors associated with the model class \( M \) and they cannot be accounted for through varying values of parameters \( \theta \). Furthermore, measurement \( y \) is equal to the real quantity \( Q \) plus a measurement error \( \epsilon_{\text{measure}} \). This relation is expressed in Eq. (1).

\[
M(\theta^*) + \epsilon_{\text{model}} = Q = y + \epsilon_{\text{measure}}
\] (1)

Therefore, by rearranging the terms of Eq. (1), the difference between a model prediction and measurement is equal to the difference between measurement and modelling errors. This relation is expressed in Eq. (2).

\[
M(\theta^*) - y = \epsilon_{\text{measure}} - \epsilon_{\text{model}}
\] (2)

Modelling error and measurement error are seldom known. Only bounds of plausible values of errors (imprecise probability) can be estimated.

Model instances are considered to be candidate models if the residual of the difference between measured and predicted values fall inside the intervals \( [T_{\text{min}}, T_{\text{max}}] \). Bounds of these intervals are obtained by computing the difference between measurement and modelling errors using elementary rules of interval arithmetic (Moore, 1966). This is expressed in Eq. (3).

\[
\epsilon_{\text{measure}} - \epsilon_{\text{model}} = [\epsilon_{\text{measure},\text{min}}, \epsilon_{\text{measure},\text{max}}] - [\epsilon_{\text{model},\text{min}}, \epsilon_{\text{model},\text{max}}] = [\epsilon_{\text{measure},\text{min}} - \epsilon_{\text{model},\text{max}}, \epsilon_{\text{measure},\text{max}} - \epsilon_{\text{model},\text{min}}]
\]

5
In this paper, the model parameters $\theta$ that need to be identified with field measurements are the wind speed and the wind direction at the inlet of the CFD simulation. The quantities compared are measured and predicted horizontal wind speeds $v_h$ as well as wind directions $\vartheta$ at sensor locations. The range of modelling error is estimated at each sensor location $i \in \{1, \ldots, n_s\}$, for each model instance $j \in \{1, \ldots, n_m\}$ and for each compared quantity $k \in \{v_h, \vartheta\}$, where $n_m$ corresponds to the number of model instances and $n_s$ corresponds to the number of sensors. At each sensor location, measured values of horizontal wind speeds $v_h$ and wind directions $\vartheta$ are compared with model predictions. Model instances $M(\theta_j)$ are candidates if, for each and every sensor location $i \in \{1, \ldots, n_s\}$ and for each and every compared quantities $k \in \{v_h, \vartheta\}$, the difference between measurement and model predictions falls inside the intervals $[T_{\min,i,j,k}, T_{\max,i,j,k}]$. This corresponds to the situation where Eq. (4) is satisfied.

$$\forall i \in \{1, \ldots, n_s\} \text{ and } \forall k \in \{v_h, \vartheta\} : T_{\min,i,j,k} \leq M(\theta_j)_{i,k} - y_{i,k} \leq T_{\max,i,j,k}$$  

Where $M(\theta_j)_{i,k}$ is the predicted value of quantity $k \in \{v_h, \vartheta\}$ at sensor location $i \in \{1, \ldots, n_s\}$ by the model instance $j \in \{1, \ldots, n_m\}$ and $y_{i,k}$ is the measured value of quantity $k$ at sensor location $i$.

Model instances that do not satisfy Eq. (4) are falsified.

3.3) Predictions of flow quantities where there are no sensors

The final candidate model set is employed to make predictions where there are no sensors. Predictions $P_{k,l}$ of flow quantities $k \in \{v_h, \vartheta, \ldots\}$ at locations where there are no sensors $l$ are calculated using Eq. (5).

$$P_{k,l} = M(\theta_j)_{i,l} + \epsilon_{\text{model},j,i,l}$$

Where $M(\theta_j)_{i,l}$ is the predicted value of quantity $k \in \{v_h, \vartheta, \ldots\}$ at a location where there are no sensors, $l$, by the candidate model $j \in \{1, \ldots, n_{\text{cand}}\}$. The term, $n_{\text{cand}}$, is the candidate-model number. $\epsilon_{\text{model},j,i,l}$ is the modelling error of the model instance $j \in \{1, \ldots, n_{\text{cand}}\}$ in the prediction of flow quantity $k \in \{v_h, \vartheta, \ldots\}$ at locations where there are no sensors $l$.

Distributions of predictions of flow quantities $k \in \{v_h, \vartheta, \ldots\}$ at locations where there are no sensors are obtained after falsification. Modelling error is then added to these distributions. Monte Carlo techniques are employed to draw samples from modelling-error distributions. Bounds of modelling error are the same as those considered for the identification of parameter values. A uniform distribution is assumed between bounds. It is common to use a uniform distribution in absence of more precise information (Goulet and Smith, 2011). For each candidate model (each plausible set of parameter values), 1000 samples are generated by adding a random value of modelling error $\epsilon_{\text{model},j,i,l}$ to the prediction of the candidate model $M(\theta_j)_{i,l}$. This results in distributions of values of flow quantity $k \in \{v_h, \vartheta, \ldots\}$ at locations where there are no sensors. Finally, ranges of predictions of flow quantity $k \in \{v_h, \vartheta, \ldots\}$ at locations where there are no sensors are calculated using a confidence level of 95%. Figure 1 summarizes the steps leading to the identification of inlet conditions given observations from measurements and the subsequent predictions of flow quantities where there are no sensors. A moving-average time series of horizontal wind speeds $v_h$ and wind directions $\vartheta$ is computed at each sensor location using the measurement data and the averaging window. The methodology is repeated for all
time steps of the time series as shown in Figure 1. Distinct sets of model instances representing sets of inlet conditions are identified at each time step.

Figure 1: Framework for the identification of plausible parameter values of CFD simulations given observations from measurements as well as the subsequent predictions of flow quantities

4) NUMERICAL SIMULATIONS

Computational fluid-dynamics (CFD) simulations have been carried out in order to simulate the airflow pattern around the “BubbleZERO”. The “BubbleZERO” is an experimental facility of the Future Cities Laboratory (FCL) Singapore-ETH Centre for Global Environmental Sustainability located at the National University of Singapore. The commercial code FLUENT 14.5 is used to solve the fluid equations of motion using the control volume method.

Only the near surroundings, including buildings and vegetation, of the “BubbleZERO” are modelled. Other buildings located within the computational domain are modelled implicitly using an increased equivalent roughness length $y_0$. Best practice guidelines were used to determine the size of the computational domain (Franke et al., 2011), creating a computational domain with dimensions length×width×height = 220m×140m×40m. CutCell meshing was employed in order to divide the computational domain into small sub-regions resulting in a grid with approximately $3.9 \times 10^5$ hexahedral cells. CutCell meshing is a method developed for FLUENT that generates a high percentage of hexahedral cells with minimal user setup. Hexahedral cells are preferable to tetrahedral cells because they introduce smaller truncation errors and provide a better iterative convergence (Franke, 2006). The expansion ratio between two adjacent cells is set to 1.1. A grid-sensitivity analysis has been performed. Two new grids consisting of $2.5 \times 10^5$ cells and $6.9 \times 10^5$ cells have been generated by varying the grid settings. The grid-sensitivity analysis has been performed only for one model instance; we assume that the grid settings defined after the analysis give good results for the other model instances. Horizontal wind-speed predictions at sensor locations have been compared for the three grids. On average, over all sensor locations, the difference between the prediction of the coarse grid and the prediction of the middle grid is 4.2% of the prediction of the middle grid. Furthermore, the difference between the prediction of the middle grid and the prediction of the fine grid is 2.7% of the prediction of the fine grid. Predictions of the middle grid do not differ significantly from those of the fine grid.
Larger differences are observed between predictions of the coarse grid and predictions of the middle grid. Therefore, the middle grid has been selected.

The SIMPLE algorithm is employed to deal with the pressure-velocity coupling (Patankar and Spalding, 1972). The second-order discretization scheme is used to interpolate pressure from the values obtained at cell centres. The convergence criteria are based on the scaled residuals for all variables, which are set to $10^{-4}$. Complexity of trees is reduced by using a tree-canopy model. Trees are modelled using a porous zone (Guo and Maghirang, 2012) defined by a level of porosity of 1 and an isotropic inertial resistance of $0.1 \text{m}^{-1}$. Isothermal simulations were performed. This can be justified due to the cloudy conditions following rain that occurred during the measurement period. The 3D steady RANS equations in combination with the Realizable k-epsilon model have been used to model the turbulent airflow.

Vertical profiles of mean wind speed $U$, turbulent kinetic energy $k$ and turbulence dissipation rate $\varepsilon$ are imposed at the inlet of the computational domain using a user-defined function (UDF) in FLUENT. The flow conditions at the inlet of the computational domain are described in Eq. (6), Eq. (7) and Eq. (8) which have been derived from neutral atmospheric conditions.

$$U(y) = \frac{u_{ABL}^*}{\kappa} \ln \left( \frac{y + y_0}{y_0} \right)$$  \hspace{1cm} (6)

$$k(y) = \frac{u_{ABL}^*}{\sqrt{C \mu}}$$  \hspace{1cm} (7)

$$\varepsilon(y) = \frac{u_{ABL}^*}{\kappa(y + y_0)}$$  \hspace{1cm} (8)

where $y$ is the height coordinate, $\kappa$ is the von Karman constant, $u_{ABL}^*$ is the atmospheric boundary layer (ABL) friction velocity and $C \mu$ is a model constant.

The standard-wall function is used to treat the near-wall behaviour of airflow (Launder and Spalding, 1974). A non-dimensional wall distance $y^+ > 30$ is achieved at all computational nodes adjacent to wall surfaces as recommended by Franke et al. (2011). In FLUENT, the sand-grain roughness $k_s$ is employed to describe the surface roughness. For the standard wall function implemented in FLUENT, a relationship between $k_s$ and the roughness length $y_0$ (commonly used in wind-engineering problems) has been established by Blocken et al. (2007). This relation is expressed in Eq. (9).

$$k_s = \frac{9.793 y_0}{C_s}$$  \hspace{1cm} (9)

where $C_s$ is the roughness constant. In FLUENT, the value of $k_s$ cannot be larger than $y_p$, which is the distance between the centroid of the wall-adjacent cell and the wall.

The roughness length $y_0$ of the atmospheric boundary layer with implicitly modelled buildings is set to $y_0 = 0.45 \text{m}$, which represent dense, low buildings (Wieringa, 1992). Therefore, values of sand-grain roughness and roughness constant have been set to $k_s = 0.73 \text{m}$ and $C_s = 6$ in FLUENT. The roughness length imposed at the ABL surface is the same as the roughness length used to compute the inlet wind profiles in order to avoid stream gradient due to roughness modification in the upstream part of the computational domain (Blocken et al., 2007). The building surfaces are defined with a zero sand-grain roughness ($k_s = 0 \text{m}$). The sides and the top of the computational domain are modelled using symmetry boundary conditions. Hence, zero normal velocity is imposed at the sides and top of the computational
The outlet of the computational domain was modelled assuming zero pressure boundary conditions.

Airflow responses depend upon the inlet conditions of the CFD simulation. In urban areas, representative values of inlet conditions are difficult to estimate or measure (Schatzmann and Leitl, 2011). In the model-based data interpretation framework, representative values of inlet conditions are identified from measurements taken in the UCL. The parameters requiring identification $\theta$ are the wind direction at the inlet $\theta_{inlet}$ as well as the reference wind speed at the inlet at 16m height $U_{ref}$. A population of model instances $M(\theta_j)$ are generated through assigning sets of parameter values $\theta_j = [\theta_{inlet,j}, U_{ref,j}]$ to a model class $M$.

A simple-grid sampling is employed in order to generate model instances uniformly within the parameter space. Table 1 presents the ranges of values of parameter requiring identification as well as their discretization intervals. The simulations were executed using 12 processes in parallel on a Windows Server 2012 containing four Hexa-Core Intel Xeon E5460 2.20GHz processors and 64 GB memory. A total of 504 simulations have been executed in batch mode which requires 48 hours of simulations using FLUENT. The outside box of the computational domain changes its orientation between runs in order to simulate different inlet wind directions $\theta_{inlet}$. This leads to the generation of a new grid for each inlet wind direction. For each model instances, horizontal wind speeds $v_h$ and wind directions $\theta$ are predicted at sensor locations. Figure 2 presents horizontal wind speeds at 1.5m height predicted with two model instances. Those two model instances are characterized by different wind directions at the inlet $\theta_{inlet}$.

<table>
<thead>
<tr>
<th>Parameter requiring identification</th>
<th>Minimal Value</th>
<th>Maximal Value</th>
<th>Discretization intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind direction at the inlet $\theta_{inlet}$ [$^\circ$]</td>
<td>0</td>
<td>360</td>
<td>10</td>
</tr>
<tr>
<td>Reference wind speed at the inlet $U_{ref}$ (at 16m height) [m/s]</td>
<td>0.5</td>
<td>7</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 1: Minimal and maximal bounds of model parameters requiring identification and size of intervals used in the simple-grid sampling
Figure 2: Horizontal wind speeds predicted by two model instances at 1.5m height. (a) $U_{ref} = 3\text{m/s}$ (at 16m height), $\theta_{inlet} = 0^\circ$. (b) $U_{ref} = 3\text{m/s}$ (at 16m height), $\theta_{inlet} = 90^\circ$, Wind from the North is at $0^\circ$.

5) EXPERIMENTAL SETUP AND FIELD MEASUREMENTS

A measurement campaign was carried out around “BubbleZERO” in order to improve our understanding of the system. The locations of the sensors are shown in Figure 3. The sensors at locations TX1, TX2 and TX4 were used to falsify model instances that are not defined with plausible sets of parameter values (inlet conditions). The sensor at location TX3 was used to validate the methodology, by treating its measurements as test data and not as “training” data used for falsifying model instances.

Measurements were made with four wind-cup anemometer positioned on tripods at heights of 1.5m or 2.5m above ground level. Sensors measure horizontal wind speeds $v_h$ as well as wind directions $\theta$. A wireless device was used to record data measured from all the wind cup anemometers simultaneously. The precisions of the sensors were 0.1m/s for horizontal wind speed measurements and 22.5° for wind direction measurements. The resolutions of the sensors were 0.4m/s. Horizontal wind speeds were sampled every 2.25 seconds while wind directions were sampled every second. Measurement data were recorded every 10 seconds. The recorded horizontal wind speed corresponded to the average value during the recording interval while the recorded wind direction corresponded to the dominant wind direction during the recording interval.
Figure 3: Picture of the “BubbleZERO” and position of wind-cup anemometers, TX.

Figure 4 presents the moving-average time series of measurements at location TX3 and TX2 using an averaging window of 90 seconds. The moving-average time series are computed by replacing the recorded value (every 10 seconds) with the 90s-averaged value of its neighbour steps. An averaging window of 90 seconds has been employed in this paper. The time variability of horizontal wind speeds is clearly observed in Figure 4. If a longer averaging window is used, the time variability of atmospheric conditions may not have been captured with the proposed model-based data interpretation framework. Measurements were carried out on 18th December 2012 from 1pm to 3pm following rain. Surface heating was negligible due to the cloudy conditions occurring during the measurement campaign.

Even though measurements were carried out at locations that are close together, variations of wind quantities are observed between measurement stations. Larger spatial variability of wind quantities might be observed if the measurement stations were located further away from each other.

Figure 4: Moving-average time series of horizontal wind speed at locations TX3 and TX2 (averaging window of 90 seconds)
6) MODELLING ERROR

An important step that determines the reliability of the identification of parameter values \( \theta = [\theta_{\text{inlet}}, U_{\text{ref}}] \) is the correct estimation of the threshold bounds \([T_{\text{min},i,j,k}, T_{\text{max},i,j,k}]\), defined by combining measurement and modelling error as expressed in Eq. (3). An estimated range of modelling error in the predictions of horizontal wind speed \( v_h \) and wind direction \( \theta \) is required for each model instance \( j \in \{1, \ldots, n_m\} \) and at each sensor location \( i \in \{1, \ldots, n_s\} \) in order to define those bounds. The goal of this Section is to define a relationship between errors associated with a RANS-based model and input/output variables of this model (e.g. errors related to the amplification factor of wind speeds as mentioned in Section 2).

Ranges of modelling error have been estimated by comparing responses of CFD simulations obtained with two turbulence models around a single bluff body having dimensions length=6.06m, width=4.88m and height=2.9m which corresponds to the building of interest in the case study presented in Section 4. Dimensions of the computational domain are length×width×height = 55.5m×31.06m×14.5m. The first turbulence model is the same as the one used for the generation of model instances \( M(\theta_j) \). This turbulence model is built on the steady RANS equations in combination with the Realizable k-epsilon model. The same numerical methods as those described in Section 4 are employed. The second turbulence model is LES using the dynamic Smagorinsky model to model the small eddies of the flow (Germano et al., 1991). Unlike RANS-based model, LES provides time-dependent predictions of flow quantities. LES has been found to be in good agreement with wind tunnel experiments (Cheng et al., 2003; Tominaga et al., 2008a) while RANS-based models have difficulties to reproduce flow separation and recirculation because of the unsteadiness of the flow field in those regions. However, since it is computationally prohibitive to perform large numbers of simulations using LES, simulations using a RANS-based model have been employed in the model-based data interpretation framework. Estimates ranges of modelling errors are determined from the differences between responses of LES and responses of the RANS-based model. A grid composed of \( 7.1 \times 10^4 \) cells is used for the RANS-based simulation and the LES. A grid-sensitivity analysis has been performed using the RANS-based model in order to define the grid settings, similarly to the analysis performed in Section 4. Scaled residuals of \( 10^{-4} \) for all variables are used as convergence criteria for the RANS-based simulation and the LES.

Other sources of error, such as those associated with geometry simplification, have not been considered. Furthermore, LES results are not perfectly correct. Thus, the threshold bounds employed in this paper are lower bound estimates.

Profiles of wind speed \( U \), turbulent kinetic energy \( k \) and turbulent dissipation energy \( \varepsilon \) imposed at the inlet of the RANS-based model are defined using Eq. (6), Eq. (7) and Eq. (8). The ground surface and building surfaces are treated with standard wall functions (Launder and Spalding, 1974) using a zero roughness length \( (y_0=0m) \). The inlet wind speed at 1.5m height is used as reference for the definition of the wind speed profile and has been set to \( U_{1.5m} = 2m/s \). The turbulence characteristics defined at the inlet of the RANS-based model are reproduced in LES by imposing a time-dependent inlet velocity profile generated using the vortex method in FLUENT 14.5. Responses of the RANS-based model are used as initial conditions for the LES simulation. A time step size of 0.1 second is used for the LES simulation. After 1 hour of real-time, representative mean values of flow quantities are reached.

In Section 6.1, responses of the RANS-based model are compared with mean responses of LES in order to estimate error of RANS-based models in the predictions of mean flow quantities.

At each time step of the time series of measurement, measured values at sensor locations are compared with model predictions. Measurements need to be averaged over a short period of time in order to
capture variation of inlet conditions with the proposed model-based data interpretation framework. In Section 6.2, LES is employed to have an estimate of error associated with fluctuations of flow quantities in which amplitude depends upon the averaging period chosen. In Section 6.3, ranges of errors are estimated for different inlet wind speeds.

6.1) Estimated ranges of error in the prediction of mean flow quantities

The differences between the mean responses of LES and the responses of the RANS-based model are employed to estimate error of RANS-based models in the predictions of mean flow quantities. Figure 5 presents the spatial distribution of these differences for predictions of mean horizontal wind speeds at 1.5m height. In this study, responses of the RANS-based model have been compared to responses of LES at 1.5m height. This corresponds approximately to half of the height of the building.

Figure 5: Differences between mean horizontal wind speeds predicted with LES and horizontal wind speeds predicted with the RANS-based model at 1.5m height (wind coming from the right).

Figure 6 shows values of differences with respect to the amplification factor of wind speeds $U/U_0$ predicted with the RANS-based model at nodes located at 1.5m height. The amplification factor of wind speeds is defined as the ratio between the local horizontal wind speed, $U$, to the horizontal wind speed, $U_0$, that would occur without buildings. In this study, $U_0$ corresponds to the inlet wind speed at the same height as the local horizontal wind speed $U$. This assumption is justified because the wind speed profile imposed at the inlet is compatible with the roughness imposed at ground level. Therefore, no stream gradient due to roughness modification in the upstream part of the computational domain is expected. It becomes clear that the range of differences is larger in the region where the amplification factor of wind speeds is less than unity ($U/U_0<1$).

Therefore, distinction is made between sensors located in the region of high wind speeds ($U/U_0>1$) and those located in the region of low wind speeds ($U/U_0<1$) in the model-based data interpretation framework. For each region, estimated bounds of error in the predictions of mean horizontal wind speeds are defined as the maximal values of differences observed in the region. Locations of these regions are different for each model instance. Ranges of error at sensor locations, and therefore threshold bounds, are adjusted depending on which region the sensor is located.
Figure 6: Differences between mean horizontal wind speeds predicted with LES and horizontal wind speeds predicted with the RANS-based model at 1.5m; $U_0=2\text{m/s}$

The same methodology is repeated in order to estimate errors of RANS-based models in the predictions of wind directions. Figure 7 presents differences between mean wind directions predicted with LES and wind directions predicted with the RANS-based model at 1.5m height. In some locations, large differences are observed. This originates from the over-estimation of the region of reverse flow in the wake of the building using RANS-based models. Therefore, RANS-based models may provide a reverse flow at some locations in the wake of the building where LES does not.

Figure 7: Differences between mean wind directions predicted with LES and wind directions predicted with the RANS-based model at 1.5m height in absolute values

Figure 8 describes values of the differences with respect to the amplification factor of wind speeds $U/U_0$. Large range of differences is observed in the region where the amplification factor of wind speeds is low $U/U_0<0.33$. In this region, the range of difference can be up to $[-180^\circ, 180^\circ]$. Therefore, sensors located in this region will not add to knowledge of airflow behaviour. In the model-based data-
interpretation framework, wind directions measured by sensors located in this region are not employed to falsify model instances. Locations of such region are different for each model instance.

Figure 8: Differences between mean wind directions predicted with LES and wind directions predicted with the RANS-based model at 1.5m height; $U_0=2m/s$

6.2) Estimated ranges of error associated with fluctuations of flow quantities due to turbulence

Discrepancies between measured and predicted values appear if the period used to average measurements is not sufficiently long because of the stochastic fluctuations of flow quantities due to turbulence.

Moving-average time series of horizontal wind speed are predicted at comparison points P1-P8 (Figure 5) using LES in order to estimate a range of error associated with fluctuations of horizontal wind speed due to turbulence. The comparison point that provides the largest fluctuations is used to estimate bounds of error. Bounds are defined as the difference between the extreme values of the moving-average time series predicted with LES and the mean value of LES. No distinction is made between the region of high wind speeds ($U/U_0>1$) and the region of low wind speeds ($U/U_0<1$).

Figure 9 presents the horizontal wind speed predicted with the RANS-based model as well as the moving-average time series predicted with LES at comparison point P1. Point P1 is the point that provides the largest fluctuations of horizontal wind speed. The red-dotted line corresponds to the value of horizontal wind speed predicted with the RANS-based model. The black-dashed line is the mean value of horizontal wind speed predicted with LES. The black line corresponds to the moving-average time series of horizontal wind speeds predicted with LES using an averaging window of 90 seconds.
The same methodology is employed to evaluate bounds of error associated with fluctuations of wind directions due to turbulence. Only comparison points characterized by an amplification factor of wind speeds $U/U_0>0.33$ (P3-P8) are considered. In order to deal with the discontinuity of wind direction between $0^\circ$ and $360^\circ$, the average value of wind direction $\bar{\theta}$ has been determined using Eq. (10).

$$\bar{\theta} = atan2(\sin \theta, \cos \theta)$$  

(10)

Where $\sin \theta$ and $\cos \theta$ correspond to the average value of the sine and cosine of the wind direction $\theta$.

It is clear that the maximal fluctuations of flow quantities depend on the averaging window chosen. Figure 10 presents the estimated bounds of error in the predictions of horizontal wind speeds and wind directions with respect to the averaging window. If the averaging window increases, the estimated ranges of error decrease.
Figure 10: Estimated bounds of errors associated with the fluctuations of flow quantities due to turbulence with respect to the averaging window. (a) Bounds of error in the predictions of horizontal wind speeds. (b) Bounds of error in the predictions of wind directions; $U_0=2\text{m/s}$

6.3) Estimated ranges of error for different inlet wind speeds

Bounds of modelling error $\epsilon_{\text{model}}$ are computed by summing the estimated bounds of error of RANS-based models in the predictions of mean flow quantities (Section 6.1) with those associated with the fluctuations of flow quantities due to turbulence (Section 6.2).

Two sets of simulations with two inlet wind speeds $U_0$ have been executed in order to evaluate the influence of the inlet wind speed on the estimated ranges of modelling error. In order to estimate ranges of error for other inlet wind speeds, a linear interpolation has been assumed. In future work, RANS-based models and LES will be compared with other inlet wind speeds in order to better define the relationship between inlet wind speed and ranges of modelling error.

Figure 11 presents the estimated ranges of error of RANS-based models in the predictions of mean flow quantities as well as the estimated ranges of error associated with the fluctuations of flow quantities due to turbulence with respect to the inlet wind speed $U_0$. Figure 12a presents the estimated ranges of errors in the predictions of horizontal wind speeds in the region of high wind speeds ($U/U_0>1$). The estimated ranges of errors in the predictions of wind speeds in the region of low wind speeds ($U/U_0<1$) are not represented in this figure. Figure 12b presents the estimated ranges of error in the predictions of wind directions in the region characterized by $U/U_0>0.33$.

7) RESULTS

7.1) Identification of inlet conditions
This Section presents the results of the model-based data interpretation framework using predictions of the model instances (Section 4), the measurement data (Section 5) as well as the knowledge of modelling errors (Section 6). In this framework, a population of model instances $M(\theta_j)$ is generated through assigning parameter values $\theta_j = [\theta_{\text{inlet}, j}, U_{\text{ref}, j}]$ to a model class $M$. Measurements are employed to falsify model instances that are not defined with plausible sets of parameter values.

Measurement errors are determined according to the precision of the sensor (Section 5). Moreover, if the measured value of horizontal wind speed is below the starting threshold of the sensor (0.4m/s), values of measurement errors are adjusted.

A study has been performed in order to evaluate errors associated with sensor-location uncertainties. In this study, one model instance has been used. For each sensor location, wind speeds and wind directions are predicted at 100 points located within a distance of 20cm from the sensor location. The maximal differences between predictions at those points and predictions at sensor locations are used to estimate these errors. The maximal range of differences for wind speeds is [-0.069m/s, 0.062m/s] and the maximal range of differences for wind directions is [-3.3°, 2.9°]. These errors have been added to the other sources of errors using elementary rules of interval arithmetic (Equation 3).

Model instances are candidates if the residual, defined as the difference between measured and predicted values of horizontal wind speed and wind direction, falls within the threshold bounds at each and every sensor location and for each and every compared quantity. In Figure 12, the final candidate model set is represented for two different time steps $t_1$ and $t_2$. Green dots correspond to candidate models while red crosses correspond to falsified models. Wind direction measured at sensor location TX2 is compared with predictions of the model instances (Figure 12a and 12b). Horizontal wind speed measured at sensor location TX2 is compared with predictions of the model instances (Figure 12c and 12d). The comparison between measured and predicted flow quantities at the other two sensor locations (TX4 and TX1) are not represented in this figure. The purple-dashed lines represent the measured values of flow quantities at location TX2. The blue lines represent the threshold bounds computed at location TX2 in order to falsify model instances using measurements.

Threshold bounds $[T_{\text{min}, i,j,k}, T_{\text{max}, i,j,k}]$ are computed at each sensor location $i \in \{TX1, TX2, TX4\}$, for each model instance $j \in \{1, \ldots, 504\}$ and for each compared quantities $k \in \{v_h, \vartheta\}$. These bounds are defined by summing the bounds of modelling and measurement error. Ranges of modelling errors are determined according to the inlet wind speed at the height of the sensor, the averaging window chosen as well as the predicted amplification factors of wind speeds at sensor locations (Section 6). Model instances are not defined by the same inlet wind speed and they don’t predict the same amplification factor of wind speed at sensor locations. Therefore, threshold bounds might be different for each model instance as shown in Figure 13.

Horizontal wind speed measured at location TX2 at time $t_1$ differs largely from horizontal wind speed measured at time $t_2$, resulting in two sets of candidate models. This highlights the dynamic identification of inlet conditions in the proposed model-based data interpretation framework. Unlike single-model approaches, the proposed framework accommodates the time variability of atmospheric conditions.
Figure 12: Comparison between measured and predicted flow quantities at location TX2. (a) Comparison of wind direction at $t_1=300s$. (b) Comparison of wind direction at $t_2=1000s$. (c) Comparison of horizontal wind speed at $t_1=300s$. (d) Comparison of horizontal wind speed at $t_2=1000s$.

Figure 13 presents the final candidate model sets obtained after falsification using measurement taken at locations TX1, TX2 and TX4 represented in the parameter space. Green dots correspond to the final candidate model set obtained at time $t_1$ while the green triangles correspond to the final candidate model set obtained at time $t_2$. Red crosses correspond to the falsified models. It becomes clear that the initial range of parameter values have been reduced through the use of measurement data taken in the UCL. At time $t_1$, the number of candidate models is reduced from 504 to 40. At time $t_2$, the number of candidate models is reduced from 504 to 16. The final candidate model set at time $t_1$ is different from the final candidate model set obtained at time $t_2$. These two final candidate model sets represent very
At each time step (every 10 seconds), the final candidate model set is employed to predict flow quantities where no measurements are carried out. Modelling uncertainty is combined to the distribution of predictions obtained with the final candidate set as explained in Section 3.3. Ranges of predictions are calculated using the uncertainty combination and a confidence level of 95%.
For validation of the proposed framework, moving-average time series of horizontal wind speeds and wind directions are computed at locations TX3 using the measurement dataset and an averaging window of 90s. At each time step, measured values of horizontal wind speeds and wind directions are compared with ranges of predictions obtained at locations TX3. It is emphasized that measurement data obtained at location TX3 was not used to identify candidate models and was used only to test whether the predictions of flow quantities are reliable.

Figure 15a presents ranges of predicted horizontal wind speeds as well as the moving-average time series of horizontal wind speeds measured at location TX3. Figure 15b presents ranges of predicted wind directions as well as the moving-average time series of wind directions measured at location TX3. Only 15 minutes of the measurement dataset are represented in these figures. If we consider the whole measurement campaign (2 hours), horizontal wind speeds measured at location TX3 fall within ranges of predictions 96% of the time. Wind directions fall within ranges of predictions 93% of the time. This demonstrates that predictions of flow quantities using the model-based data-interpretation framework at location TX3 are fairly reliable.

Other sources of modelling error such as geometry simplification need to be considered in the model falsification approach in order to improve the reliability of identification and subsequent predictions. Moreover, the modelling errors have been estimated by comparing responses of a RANS-based model with those of LES. Although LES is more accurate than RANS-based in regions of flow separation and recirculation, LES is not an exact representation of reality. Therefore, only lower bound estimates of modelling errors are determined in this paper.

Figure 15: Ranges of predictions as well as the moving-average time series of flow quantities at location TX3 (averaging window of 90 seconds)

8) DISCUSSION

This paper proposed a model-based data interpretation framework for the assessment of airflow in urban areas. In this framework, predictions obtained with CFD simulations are integrated with data obtained with measurements as well as with knowledge of uncertainties in order to improve the accuracy of airflow predictions in urban areas. A systematic approach for the estimation of modelling error associated with RANS-based models has been incorporated to this framework. The results show that predictions in terms of mean wind speeds and mean wind directions are more accurate in regions of high wind speeds (high amplification factor of wind speeds) than in regions of low wind speeds. This is in agreement with recent work by Blocken et al. (2011) on the performance of RANS-based models for airflow modelling using CFD simulations. The framework accommodates the time variability of atmospheric conditions by 1) identifying different sets of boundary conditions at each time step and by
2) adding additional source of errors associated with the fluctuations of flow quantities during the computation of thresholds bounds.

There are (of course) limitations. In the present study, only inlet conditions have been identified using measurements taken in the UCL. Other parameters that may influence the airflow around buildings, such as the roughness of the surrounding buildings or the inertial resistance of trees, have not been considered. In further studies, more parameters will be identified that have varying values with respect to time (e.g. inlet conditions) as well as constant values with respect to time (e.g. roughness of buildings). A grid-based sampling has been used for the generation of model instances in this work. In this approach, the size of the initial candidate model set increases exponentially with the number of parameters requiring identification. More efficient techniques may be used in order to decrease the complexity of sampling in high-dimensional parameter space. Moreover, if many parameter values need to be identified, care is needed in order to avoid parameter compensation at sensor locations.

CFD simulations have been performed on small-size buildings. Only the “BubbleZERO” and its near-surroundings are explicitly modelled. Therefore the computational domain is relatively small (length×width×height=220m×140m×40m). Sensors used in this study are located close to each other and therefore, the spatial variability of airflow is not well-pronounced. In future work, the framework will be tested and validated in a case study with larger computational domain and taller buildings. More sensors will be employed and they will be located further away from each other.

In this paper, only modelling errors in the predictions of mean flow quantities using RANS-based models as well as errors associated with fluctuations of flow quantities have been acknowledged. The modelling errors have been defined by comparing responses of a RANS-based model with those of LES around an isolated building with a cubical shape. Although LES is clearly more accurate than RANS-based models in the predictions of mean flow characteristics, LES does not perfectly simulate the airflow behaviour around buildings (Lim et al., 2009; Tominaga et al., 2008a).

Moreover, in other building configurations, ranges of errors as well as their relationship with the amplification factor of wind speeds or the averaging window may differ from those obtained in the present study. Furthermore, other sources of errors need to be considered in order to predict more reliable ranges of predictions at locations where there are no sensors. Sources include simplifications of urban shapes, idealisation of boundary conditions with a logarithmic profile that has been derived for neutral conditions as well as the assumption that thermal processes, such as convection, are negligible. Also, errors due to values of parameters that are difficult to quantify and that have not been identified, such as the roughness of the surrounding buildings or the inertial resistance of trees, influence reliability. Finally, the proposed methodology used to estimate spatial variations of ranges of modelling errors depending on the predicted amplification factor of wind speeds should help define optimal sensor configurations in further studies.

### 9) CONCLUSIONS

This work has led to the following conclusions:

1) The model-falsification methodology has much potential for interpreting sensor measurements to improve the accuracy of airflow simulations around buildings.

2) Adapting the error-domain model falsification approach to represent the dynamic behaviour of airflow has successfully led to narrowing down several hundred parameter-value sets to a few possible inlet conditions for the selected case-study. Thus the case-study illustrates an approach for identifying time-varying inlet conditions and predicting wind characteristics at locations where there are no sensors.
3) Modelling errors need to be recognized and quantified in order to perform reliable predictions of airflow characteristics at locations where there are no-sensors. Ranges of modelling errors depend on the predicted amplification factor of wind speeds, the wind speed at the inlet as well as the time period employed to average measurement data.

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